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Key Parameters and Efficiency of Mexican Manufacturing – Are There Still Differences between the North and the South?

An Application of Nested and Stochastic Frontier Panel Data Models

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ABSTRACT

This study explores the prevalence and nature of the regional divide for the Mexican manufacturing production across sub-national regions. We utilize a unique panel of municipality-level data from the manufacturing sector. An important contribution is the use of different panel methods to account for latent regional characteristics and the computation of performance indicators for each municipality which will enable detailed regional rankings.

Firstly, we apply nested panel methods to estimate regional production functions and to analyze production characteristics and scale economies. Subsequently, we use stochastic frontier analysis methods to test for productivity and efficiency differences in manufacturing throughout the country.

Our results suggest that the economic structure and productivity of southern Mexico is considerably different from the centrally located manufacturing belt and the north. Remarkably, rankings based on nested panel and stochastic frontier estimations confirm very similar regional patterns. Nevertheless, efficiency varies strongly within states, indicating that 'islands of excellence' prevail in otherwise highly inefficient and lagging states.

Keywords: *Mexico, Manufacturing, Efficiency Analysis, Stochastic Frontier Analysis, Panel Data Models*
JEL classifications: *C23, D24, O18*

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1) Introduction

Mexico represents a particularly interesting and relevant case for studying the distribution of economic activity across space due to its prevailing regional disparity. Pronounced lines of divide are running between the urban and rural and even more so between the northern and southern areas. Such geographical and sub-national conditions are receiving growing attention as channels of growth dynamics, thereby digressing from the view that developing countries across all regional levels are equivalently capable to absorb technology, grow or even converge with developed economies.

North-south disparity within a country is not an uncommon phenomenon, one prominent example being Italy; Mexico is however especially interesting due to its unique location as an industrializing country neighboring the world's largest economy, the U.S. The regional divide manifests itself in widespread poverty, rudimentary infrastructure, high shares of indigenous population and in underdeveloped activities of the productive sector of the southern periphery.

Mexico has been afflicted with regional differences and marginalization at least since colonization. Most of the wealth originated from mining in the north of the country at that time, favoring the development of these regions and the capital city. After Mexico followed a factual import substitution strategy since the 1940s, the manufacturing industry agglomerated at the Greater Mexico City Area. The New Economic Geography relates such location patterns to firms and industries exploiting location advantages of backward-forward linkages in the center, specifically proximity to suppliers and to the home market, and knowledge spillovers in a world with costly trade (Krugmann 1991). The self-reinforcing nature of agglomeration dynamics has been additionally spurred by Mexico city's large and ever-growing labor pool, its location at the core of the radial railway and motorway network and regional policies being biased towards the capital.

Over the last decades, trade liberalization and growing integration with Northern America have fueled manufacturing exports and remarkably altered regional structures. The south may have comparative advantages related to its crucial resources like oil and natural gas, favorable climate and hydration, but low transportation costs to the major trading partner have rather promoted new and specialized industrial centers at the northern border at the expense of the traditional manufacturing belt around Mexico City (Hanson 1998). Plenty of these sites are *maquiladoras* which have been established by the Border Industrialization Program of 1965 as in-bond plants to assemble semi-finished inputs and to re-export the final goods like electronic equipment free of duty. *Maquiladoras* have as well been set up in non-border regions later on, though sparsely in the south (MacLachlan and Aguilar 1998).[1]

Manufacturing production is of great relevance, as it exerts profound influence on the country's modernization process, income generation and distribution and has traditionally drawn considerable attention of policy makers. We therefore consider it a meaningful approach to empirically explore the characteristics and performance of the Mexican manufacturing sector at detailed sub-national level. Our analysis builds on a unique panel comprising the majority of Mexican municipalities (2038 out of 2452) over the period 1989 to 2004 - a time horizon including major changes such as the disruptive period of the 1994/1995 economic crisis and the formation of the NAFTA.

The outline of the paper is as follows: section 2 reviews central underpinnings of theories of production, followed by a presentation of the empirical framework with recent panel approaches as the nested error component model (NECM) and stochastic frontier analyses (SFA). Subsequently, section 3 introduces and surveys the database. Section 4 summarizes the most prominent empirical findings and highlights important implications. Last section 5 concludes.

1 Maquiladoras no longer exist in a narrow sense after registration obligations and tariff preferential treatments have been fully phased out due to the NAFTA in 2001.

2) Theoretical Background and Econometric Specifications

2.1 Production Economics

The technological possibilities of firms and industries can be summarized by means of production functions which represent the technical relationship between the level of inputs and the resulting level of outputs.[2] An econometric production function estimation from observed input output combinations therefore determines the average level of outputs that can be produced from a given level of inputs (Schmidt 1986). Production function estimation can be applied to firm-level data, as well as to analyze aggregated production within regions, municipalities or states. Different algebraic forms can describe the technology of the industry.[3] The most frequently used in empirical application are the Cobb-Douglas[4] and the Translog which depend on different assumptions regarding returns to scale and substitution elasticities.

The Translog function which we will use in the empirical analysis is defined by a second order (all cross-terms included) log-linear form and represents a relatively flexible functional form, as it does not impose assumptions about constant elasticities of production nor elasticities of substitution between inputs (see Coelli et al. 2005).[5]

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[2] The principal properties of production functions that underpin the economic analysis are non-negativity, weak essentiality, non-decreasing and concavity in the different inputs (see Coelli et al. 2005 and Chambers 1988).

[3] Among the most important are the linear, the quadratic, the normalized quadratic, the generalized Leontief and the constant elasticity of substitution (CES) function.

[4] The Cobb-Douglas production function is characterized by more restrictive assumptions regarding returns to scale and the elasticity of substitution. The elasticity of substitution has a constant value of one - i.e. the functional form assumption imposes a fixed degree of substitutability on all inputs - and the elasticity of production is constant for all inputs. The Cobb-Douglas is a special case of the Translog production function for all β_{km} being zero.

[5] It thus allows the data to indicate the actual curvature of the function, rather than imposing a priori assumptions.

The multiple-input Translog production function in a general form is defined as:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{km} \ln x_{kit} \ln x_{m}it$$

Where $\ln y$ represents the output in a log form, $\ln x_k$ represents the different inputs, $\ln x_k \ln x_m$ the different squared and cross terms; β_0 the intercept or the constant term; and β_k and β_{km}s are the parameters to be estimated. Within this framework a Hicks-neutral technical change is assumed; this means that the marginal rate of technical substitution is independent of time.

2.2 The Unbalanced Nested Error Component Model

The previous theoretical considerations serve as the base for an empirical model of regional production. We just present the econometric specification of the Translog specification; assumptions and reasoning are equivalently valid and applicable for the Cobb-Douglas function, as the latter is a special case of the former. The basic empirical representation is then as follows:

$$y_{jt} = \beta_0 + \beta_1 fa_{jt} + \beta_2 lj_t + 0.5\beta_3 l_{jt}^2 + 0.5\beta_4 fa_{jt}^2 + \beta_5 l_{jt} fa_{jt} + \varepsilon_{jt}, \quad j = 1, ...n; t = 1,...3 \quad (1)$$

Index j refers to the respective municipality with n equal to 2038 and t indexes time, specifically the years 1989, 1999 and 2004, y_{jt} is the dependant variable, it is the natural logarithm of (real) value added, fa_{jt} the logarithm of the (real) capital stock and l_{it} the logarithm of the number of employees (see section 3 for a detailed presentation of the selected variables).

A pooled Least Squares (LS) estimation of equation (1) represents the base approach for our analysis. ε_{jt} is assumed to have zero mean and to be identically and independently distributed (over time and municipalities): $\varepsilon_{jt} \sim IID\left(0, \sigma_{\varepsilon}^{2}\right)$. Given these assumptions, estimates will be unbiased and efficient. The error term reflects measurement errors or mal-specifications, but is as well likely to contain shocks unknown to the researcher - but not to the decision-making units. As these unobserved elements are likely to adhere to a regional pattern and to exert a role in the production environment, further attention is directed at the error specifications and refinements of modeling unobserved heterogeneity. Examples of these regional effects can be state-related corporate tax settings, climate conditions and location or transportation infrastructure.

We therefore proceed to an econometric model that addresses these shortcomings. An interesting feature of our dataset is its inherent natural grouping; each municipality is uniquely subordinated to one of the 32 states of Mexico (see Figure 1 and Table 2). Facing this nested structure, it is plausible that individual effects are associated with both state- and municipality-level. Unobserved factors such as railway connectivity or port access can be supposed to be municipality-specific, whereas corporate tax settings or production subsidies as state-specific. To account for this structure, we keep our basic Translog respectively Cobb-Douglas specifications, but we adopt a single-nested error components model as suggested by Baltagi et al. 2001. It follows then:

$$\begin{aligned} y_{ijt} &= \beta_0 + \beta_1 fa_{ijt} + \beta_2 l_{ijt} + 0.5\beta_3 l_{ijt}^2 + 0.5\beta_4 fa_{ijt}^2 + \beta_5 l_{ijt} fa_{ijt} + \varepsilon_{ijt}, \\ &\quad \text{where } i = 1,....32 \quad j = 1, ...n_i;\ t = 1,...3 \end{aligned} \tag{2}$$

The model has one time-series dimension t, but two cross-section dimensions; as before index j refers to the j^{th} municipality – but nested in state i here. The model is appropriate for our panel which is unbalanced in the sense that the number of municipalities per state, n_i, differs from state to state (see Table 2). It utilizes a two-way error components specification as follows: μ_i represents the unobserved specific effect of state i and is assumed to be $\mathrm{IID}(0,\sigma_\mu^2)$, the effect υ_{ij} of the j[th] municipality in state i is assumed to be $\mathrm{IID}(0,\sigma_\upsilon^2)$ and ε_{ijt} is the remainder disturbance such as measurement errors or unforeseen shocks, again $\mathrm{IID}(0,\sigma_\varepsilon^2)$. All three error components are further mutually independent from each other.

The distribution of the random state- and municipality-specific effects plays a role through the estimates of the variance components. LS yields unbiased and consistent estimates if the variance components σ_υ^2 and σ_μ^2 are zero - however biased standard errors if variance components are nonzero. A consistent and efficient estimation of the random factors of the single-nested structure model can be obtained by the restricted maximum likelihood approach (REML) (Baltagi et al. 2001). This is based on partitioning the likelihood function and maximizing that part of the likelihood function which contains only variance components and no regression coefficients (for further details see Patterson and Thompson 1971).

Monte-Carlo studies by Baltagi et al. 2001 have shown that REML estimators perform specifically well in estimation of variance components, as well as for data with pronounced unbalanced pattern, but slightly less so with respect to regression coefficients. Being aware of this caveat, we have however preferred the more popular REML or alternatively maximum likelihood (ML) to other ANOVA-type approaches.

2.3 Efficiency and Productivity Analysis

We further want to relate our findings of the nested error component model to an econometric frontier efficiency analysis of the different municipalities in order to get an insight of the ranking and individual efficiencies of the municipalities.

First of all we want to test on municipality if larger municipalities in the north operate more efficient. Further, we want to figure out factors for explaining efficiency differentials.

We herby focus on different models of the stochastic frontier analysis (SFA). The SFA is a parametric approach for frontier estimation able to differentiate between efficient and less efficient decision making units, in our case the municipalities.[6] Within this approach we assume a given functional form of the relationship between inputs and outputs and estimate the unknown parameters of the function by maximum likelihood techniques. Contrary to a Least Squares regression, the stochastic frontier model decomposes the residuals into two terms, a symmetric component representing statistical noise, and an asymmetric component representing inefficiency (see Greene 2004).[7] The most general formulation, proposed by Aigner et al. 1977 is as follows (see Greene 2004):

$$\begin{aligned} & y = \beta' x + v - u, \\ & u = |U| \\ & U \sim N[0, \sigma_u{}^2] \\ & v \sim N[0, \sigma_v{}^2] \end{aligned} \tag{3}$$

where x represents the set of explanatory variables (inputs in the case of a production frontier), y the observed production of a firm; u represents the nonnegative random variable associated with inefficiency following a half normal distribution, and *v* the symmetric random error accounting for noise. For the noise component v it is assumed that they are independently and identically distributed normal random variables with zero means and variances. As the model is usually specified in natural logs, the inefficiency term u can be interpreted as the percentage deviation of observed performance y from the unit's own frontier performance (see Greene 2002).[8]

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[6] Other parametric non stochastic approaches are the corrected ordinary least squares (COLS) and the modified ordinary least squares (MOLS).

[7] The theory of stochastic frontier production functions was originally proposed by Aigner et al. 1977 as well as Meeusen and van den Broeck 1977.

[8] A large number of variants of the stochastic frontier model with regard to the distributional specifications of the inefficiency u have been proposed in the literature. In addition to the half normal distribution of u there are three further common alternatives: the truncated normal (see Stevenson 1980), the exponential and the gamma model (see Greene 1990). An extensive survey of the different models can be found in Kumbhakar and Lovell 2000 who also provide the likelihood functions for the different models for estimation purposes.

Stochastic frontier analysis allows the computation of efficiencies of the individual decision units or the whole industry. A common measure of technical efficiency is the ratio of the observed output to the corresponding stochastic frontier output (see Coelli et al. 2005). In a general form, for both approaches, relative to the production frontier, the measures of technical efficiency TE are defined as:

$$TE = E(y|u,x) / E(y|u=0,x) = Exp(-u) \tag{4}$$

where E is the conditional expectation (see Coelli et al. 2005). TE takes a value between zero and one and indicates the observed output of the j^{th} unit relative to the output which could be produced by a fully efficient unit using the same input vector (production function approach). The above measures of technical efficiency rely upon the predicted value of the unobservable u (see Coelli et al. 2005). It is determined by means of conditional expectations of the functions of u, conditional upon the observed value of the whole error term:

$$\nu - u$$ [9]

We apply two different panel data specifications for SFA: the so called "true" random effects model (see Greene 2004, 2005) as well as the random effects specification by Battese and Coelli 1995. The first model allows for considering time invariant unobserved factors within the econometric specification in order to have a more robust and reliable ranking of the estimated technical efficiencies of the municipalities. With the second model we want to test if infrastructural conditions have a significant impact on the efficiency differences across municipalities. All models are based on the specification of inputs and outputs introduced in section 2.1. The specification of the random error varies across the specification. The

[9] Jondrow et al. 1982 and Battese and Coelli 1992 derive the conditional predictor of u in detail.

following Table 1 provides a summary of the different model specifications and a description of the stochastic terms included in the model. Randomly distributed unit specific effects and error terms are added to the core specification. For a derivation of the estimation procedure as well as the respective maximum likelihood functions see Greene 2004, 2005 and Battese and Coelli 1995.

Table 1 Model Specification for Stochastic Frontier Models

	Model I True Random Effects Model (TRE Model)	Model II Random Effects Model (Battese and Coelli 1995)
Functional form	$y_{it} = \alpha_i + \beta' x_{it} + \varepsilon_{it}$	$y_{it} = \beta' x_{it} + \varepsilon_{it}$
Unit-specific component α_i	$\alpha_i \sim N(0, \sigma_\alpha{}^2)$	-
Random Error ε_{it}	$\varepsilon_{it} = v_{it} - u_{it}$ $u_{it} \sim N^+(0, \sigma_u{}^2)$ $v_{it} \sim N(0, \sigma_v{}^2)$	$\varepsilon_{it} = v_{it} - u_i$ $u_i \sim N^+(\gamma' z, \sigma_u{}^2)$ $v_{it} \sim N(0, \sigma_v{}^2)$

Greene 2005

Model I deals with the following shortcomings of the traditional fixed and random effects models for stochastic frontiers (see e.g. Pitt and Lee 1981 for the random effects model for stochastic frontier models, or Schmidt and Sickles 1984 for the fixed effects model for stochastic frontiers): First, efficiency estimation in the traditional stochastic frontier models typically assumes that the underlying production technology is the same for all units. There might, however, be unobserved differences in technologies that would be inappropriately labeled as inefficiency if such variations in technology are not taken into account. Greene 2005 summarizes that the models fail to distinguish between cross individual heterogeneity and inefficiency, because “fixed and random effects estimators force any time-invariant cross unit heterogeneity into the same term that is used to capture the inefficiency”. Another shortcoming is that the conventional estimators assume inefficiency constant over time.[10] The TRE model also belongs to the classes of normal-half normal stochastic frontier model.[11]

Therefore the basic underlying assumption of this model is the existence of unit-specific and time-invariant factors that cannot be captured by environmental variables due to the variation of the latter over time and/or omitted variables. The model can be interpreted as a random-constant frontier model based on the structure of a normal, half-normal stochastic frontier model. With the additional inclusion of heterogeneity terms by means of the random unit-specific effect α_i, the model is expected to provide a better distinction between inefficiency and other unexplained factors.[12]

Battese and Coelli 1995

Battese and Coelli 1995 proposed a random effects model for stochastic frontiers to measure technical efficiencies which have been adjusted to account for environmental influences such as geographical factors or infrastructural conditions, etc. We observe that two alternative approaches to this problem have been proposed in the efficiency measurement literature. One assumes that the environmental factors influence the shape of the technology while the other assumes that they directly influence the degree of technical inefficiency. The Battese and Coelli approach is based on the second one where environmental observable factors z directly influence the stochastic component with $u_i \sim N^+(\gamma' z, \sigma_u^2)$ see Table 1.

The empirical results of both model specifications on the estimation outcomes and the inefficiency estimates are studied by a comparative analysis.

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[10] There are models relaxing the time invariance (see e.g. Battese and Coelli 1992, Lee and Schmidt 1993, Kumbhakar 1993), however the random component is still time-invariant which remains a substantive and detrimental restriction.

[11] Greene 2007 points out that it seems to be a model with three part disturbances which is certainly inestimable. Greene 2007 shows that this is not correct; it is a model with a time traditional random effect, with a further characteristic that the time-varying disturbance is not normally distributed.

[12] The true random effects model can be seen as a special case of the random parameters model, where the only random parameter in the model is the constant term. The model can be estimated by means of simulated maximum likelihood. For details on the estimation procedure and the identification problem mentioned previously see Greene 2004, 2005 and 2007.

3) Data Description

The empirical model is estimated using a balanced panel based on regional production data of the manufacturing sector. Data have been taken from the economic census of the Mexican national statistical office *"Instituto Nacional de Estadística Geografía e Informática"* (INEGI). It is available for all municipalities (around 2400), each subordinated to one of the 32 Mexican states (see Figure 1 and Table 2), and for the years 1989, 1999 and 2004.[13] We are utilizing gross value added Y_{jt} as a proxy for output and the inputs stock of private capital Fa_{jt} and number of persons employed L_{jt} for our analysis. These variables are commonly used in estimations of conventional and regional production functions see e.g. Gerking 1994 or Hsing 1996. We implicitly assume that land use, labor quality, etc. are essentially invariable over our short panel period. Further note that the panel completely excludes economic activity of the informal sector which plays notwithstanding a substantial role in Mexico.

For selected SFA applications we additionally utilize two structural variables as an indication for the regional production environment. To account for the role of infrastructure services we include the proportion of households accessing piped water from the public line onto their estate (Whh_{jt}) and secondly the share of households connected to the electric grid ($Elhh_{jt}$). Both variables are being used since prior studies have pointed out to the notable differences in size and significance of differentiated infrastructure categories than in the case of a single composite public infrastructure index (see Garcia-Milà et al. 1996).

Monetary series value added and private capital stocks were deflated by the Banxico "Producer price index for finished goods excluding oil" to capture these variables in their real terms. Adjustments were undertaken with respect to the base period December 2003. By

[13] Due to inconsistent reporting of variables for the year 1994, data from this year could not be considered in our panel. For all further analyses we therefore employ a balanced panel *excluding* the year 1994.

using a single national deflator, the law of one price is implicitly assumed. This is adequate if markets are not regionally segmented and companies serve the entire national or international market at competitive prices. The plausibility of this implicit assumption can unfortunately rarely be tested as regional price data are not reported in the required detail for most countries, including Mexico.

Additionally, variables have been mean-corrected and transformed with natural logarithm to minimize the leverage of outliers and for ease of interpretation as straightforward elasticities with respect to value added (variables henceforth denoted with small letters). We have dropped all municipalities that do not report any production activity or have been newly constituted over the panel horizon, and we finally base our analysis on a balanced panel of 6144 municipalities over the period 1989 to 2004 (see Table 2).

Descriptive statistics in Table 3 reveal notable variations of production variables such as (real) value added with a mean of 448917 Peso and a standard deviation of 2226472 for 2004. The overall average employment is 1800 persons per municipality, with the highest mean value of 2132.96 in 1999 and again substantial variations. Concerning the proxies for the production environment, access to water is clearly lower than access to electricity (788% respectively 29% in 1989), with both of them rising over time. Of special interest is the regional dimension of these variations, as provided by Table 2. The last but one column displays sizeable disparities in average value added per worker across the states. Remarkably, the southern state of Tabasco is featuring a high level of this raw measure of productivity (119 Pesos per worker), followed by the traditional manufacturing centre Distrito Federal (D.F.). Among the lower performing states are primarily southern ones such as Yucatan, Guerrero and Oaxaca (around 20 Peso per worker).

The ratio of labor input per state relative to the national level is shown in the last column. The long-established and centrally located manufacturing agglomerations of Mexico and D.F. have the highest relative employment, whereas the lowest are in the northern state Baja

California Sur and in the southern Quintana Roo. Careful introspection of these figures indicates a strong role of the old industrial centre of Mexico City and a less clear-cut picture concerning the north-south divide.

4) Empirical Results

4.1 Nested Error Component Models

Estimation results from the pooled Least Squares and error components estimations for the Translog and Cobb-Douglas case are provided in Table 4. A comparison of estimated elasticities is unfortunately rarely feasible, as equivalent studies have so far been only conducted on firm-level for Mexico (see for example Salgado Banda and Bernal Verdugo 2007), respectively regional approaches only for developed countries (however, often with disparate methods and results, for an overview see Gerking 1994). As variables have been normalized by mean-correction, coefficients can be interpreted as output elasticities with respect to capital and labor for the average unit considered.

LS estimation of the Translog production function yields significant and positive estimates of the coefficients – with the exception of the insignificant quadratic capital term. The elasticity of output – here represented by (real) value added - with respect to the input labor is 0.613 and to capital is 0.525. The significant estimate of the quadratic labor term is positive (0.04), whereas the cross term is significantly negative (-0.016) - indicating substitutability of capital and labor inputs. We additionally test whether the production characteristics exhibit constant returns to scale, i.e. the joint hypothesis that the coefficients of squared and cross terms are insignificant and that those of capital and labor add up to one. This hypothesis is rejected, and there is clear evidence for variable, specifically increasing returns to scale ($F(3, 6108)$: 426.33).

In the Cobb-Douglas case all estimates are significantly estimated. However, when comparing between the two functional forms, the estimate for capital has risen (0.525 vs. 0.572), whereas that for labor is rather lower (0.613 respectively 0.589) for the Cobb-Douglas form. The coefficient of determination in the Translog case is notable higher than in the Cobb-Douglas case (0.947 vs. 0.718), a slight indication in favor of the more flexible Translog form.

Secondly, we proceed to a discussion of the results of the single-nested error components model which relies on a more adequate description of the unobserved regional components. The sign of the estimated coefficients resemble those of the LS estimation. Similarly, the coefficient of the quadratic term for capital is insignificant and the interaction of labor and capital is significantly positive. We refrain here from discussing coefficient estimates and their interpretations from the Cobb-Douglas form in detail, because they reveal somewhat similar insights from what has been discussed before for the LS case.

The variance components are of special relevance in the nested error component specification. In the Translog case the estimated variance of the state-effects ($\sigma_\mu : 0.264$) is lower than for the municipality-effect ($\sigma_\upsilon :$ 0.152) which is in turn clearly smaller than the idiosyncratic variance ($\sigma_\varepsilon : 0.648$). All variance components are significantly different from zero which is an indication against the validity of a LS approach, since standard errors obtained from LS are biased whenever variance components are non-zero (Baltagi et al. 2001).

To discriminate between the two production functions, we have employed a Likelihood Ratio test for the nested ECM case.[14] We can clearly reject the hypothesis that the log-likelihood function evaluated at the restricted (Cobb-Douglas) and unrestricted (Translog)

[14] The fixed effects part (i.e. the coefficient sets) of the NECM is differently specified in the Cobb-Douglas than in the Translog case which REML thus estimates as separate models. LR-tests for comparing models with different parameterizations of the FE-part are not possible then. Alternatively, models have been re-estimated with ML. Coefficient estimates from this ML estimation are very close to those obtained by REML.

model are not significantly different from zero (see Table 4). Underlying technology is thus not characterized by constant returns to scale over all levels of inputs, and we favor the more flexible Translog against the Cobb-Douglas model.

Apart from estimating the variance components and coefficients itself, we are additionally interested in obtaining the municipality- and state-specific intercepts with best linear unbiased predictions (BLUPs) in order to explore the actual regional differences. The ECM specification is especially suitable for our research question, as it is able to reveal the different relevance of unobserved factors depending on the respective regional level. Such level differences of regional production functions are considered as an indication for the level of technological development of the respective regional economy. Table 5 displays the systematic differences in size and sign of the intercepts between the states. These neutral shifts in the production functions at either state- or municipality-level are typically both negative for the Southern Highland states as Guerrero or the Yucatán Peninsula, but large and positive for the northern border states of Sonora or Chihuahua. The predicted intercepts on state-level are usually much higher than for the municipality. However, the variation among and within the states is substantial indicating that the perception of a north-south divide should be discussed cautiously under this reverse and on sufficiently detailed regional level.

Table 6 shows the ten highest and lowest ranking municipalities according to the size of their aggregated state- and municipality-level effects. Among the top municipalities is for example Naco, Sonora, whose high positive level-shift can be presumed to be associated with its location as a twin border town with Naco, Arizona. Many of the low municipalities typically stem from the southern periphery, but interestingly one can find several municipalities from mediocre or low-performing states among the top 20 ranking municipalities as e.g. Cuautinchán from Puebla.[15] Careful introspection of the regional effects thus provides evidence in favor of a north-south divide, but as well points out to the sizeable

[15] Detailed lists of the ranking of the states and municipalities are available from the authors.

variation within the states – a phenomenon demonstrating that municipalities “flourish” in otherwise desolate states.

4.2 Stochastic Frontier Analysis

We now turn to the results of the parametric stochastic frontier analysis in order to analyze the efficiency differences on municipality- and state-level.[16] With the SFA results we want in a first step test with Model I the hypothesis if there are still large and sustained differences between the municipalities in the north and the south of the country. In a second step we want to figure out with Model II if infrastructural differences have a significant impact on the efficiency levels and could therefore help to explain the efficiency differences. We start with the estimation of a true random effects model according to the Greene 2005. The estimation results are summarized in Table 7.

We have suggested the TRE (2004, 2005) model to overcome the problem that any unobserved time-invariant, but municipality-specific heterogeneity is considered as inefficiency. We focus in our analysis on the random effects specification outlined in section 2.3.[17] Estimation results show that the coefficients remain approximately the same, the estimated coefficients of labor and capital elasticities reflect the same trend as in the nested error components models.

Special interest of the analysis lies in the estimation of the individual efficiencies of the municipalities in the sample.[18] The hypothesis is that larger municipalities in the north of the country operate in a more productive and more efficient way. Table 8 summarizes the mean technical efficiencies and their standard deviations on state-level for the different SFA specifications. The mean technical efficiency level in the manufacturing sector is 0.67 across

[16] We assumed for all SFA Models the more appropriate Translog specification, as shown in section 4.1. Predicted technical inefficiencies were calculated according to Jondrow 1982.
[17] The simulated maximum likelihood estimates as well as the inefficiency predictions were obtained using LIMDEP Version 9.0 (Greene 2007).
[18] As outlined in section 2.3, the efficiency of the municipalities would be: $\text{Efficiency} = \exp(-u)$.

all states. This means that on average the same output could be produced with only 67 per cent of the actual input.

We have then proceeded to analyze the different performance levels of the states. For this purpose we have calculated the average of the technical efficiency on municipality-level for each of the 32 states. It can be seen from Table 8 that Sonora, Chihuahua, Nuevo Leon, Coahuila de Zaragoza are among the best performing states. All lie at the US border in the north of the country. When we consider the worst performing states, we identify Oaxaca, Guerreo and Yucatán, all of them in the southern part of the country. Thus the empirical analysis confirms the hypothesis: large and sustained differences are still prevalent in the economic structure and performance of sub-national regions in Mexico. Southern states and municipalities still appear to suffer from a lack of technical efficiency in comparison to the north. This might be explained by the geographical closeness to the American boarder where the northern regions benefit from the connectivity to trans-border markets in the United States. A considerably different industrial structure of the south in comparison to the north might be another reason. Further, the south is dominated by micro firms with low-skilled employees; labor productivity is accordingly very low. The southern states are additionally confronted with lower levels of transport connectivity in opposition to the northern regions.

It is also important to know to which extent the technical efficiency scores vary in each region to figure out the disparity in each state. We have obtained the standard deviation in each state and can observe that the states with a very low technical efficiency score feature a high standard deviation which indicates a high disparity in these states, as e.g. in Oaxaca and Nayarit. Thus, there are also municipalities which operate in a more efficient way. The disparity is also reflected when we do not look at the average in each state, but at the individual scores on municipality-level.

Within this framework we find that the most productive municipality is Urique in Chihuahua, Hidalgo in Durango, Cuautinchán in Puebla and Malinaltepec in Guerrero. The best and worst performing municipalities are outlined in Table 9. This shows that there are municipalities performing indeed very well in Oaxaca. The least productive municipalities are Tahmek, Quiriego and Yaxkukul.

In Model II we explicitly take into account different infrastructural conditions of the municipality. We utilize the proportion of households with electricity as well as water access as proxies for the infrastructure conditions of regional production and test whether these variables have a significant impact on explaining the efficiency differences. The estimation output is shown by Table 7. The average efficiency estimates are outlined in Table 8. The relative water access is significant at the 5% level, whereas the variable electricity connectivity is not. Thus, the extent of penetration of the water network is a relevant factor for explaining the productivity and efficiency differentials across the municipalities, whereas electricity plays a negligible role in this regard. This surely reflects the pivotal role of water resources in the largely arid and semi-arid country, for which issues of water quality and connectivity have been frequently identified as serious risk factors for any economic activity (see for example Asad and Dinar 2006).

The average technical efficiency in the Battese and Coelli 1995 specification is lower in comparison to the true random specification (Greene 2004 and 2005). This underpins the assumption that in the Battese and Coelli 1995 specification the inefficiency term also contains all other time invariant unmeasured sources of heterogeneity (see Greene 2005). In the true random effects model theses effects appears in the random constant. We can conclude that the inefficiency estimates are sensitive to the specification of unobserved community-specific heterogeneity, and therefore the inefficiency scores obtained from the traditional specifications (including unobserved environmental factors) most likely overstate the inefficiency of the municipalities. However, the overall trend found in the other models remains valid: a substantial efficiency divide can be identified between the more efficiently operating northern municipalities and their southern lagging counterparts.

5) Conclusion

In this paper, we analyzed the key characteristics of Mexican manufacturing on a regional disaggregated level. Using a balanced panel of municipality-level data from INEGI, we explore the hypothesis if there still are marked differences in the economic structure and productivity among the 32 states and their municipalities. We utilize regional production functions to describe production characteristics and technology in the spatial dimension. A special emphasis is given to explore the prevalence and dimension of these differentials, particularly along the north-south line. An important issue is to adequately address the presence of unobserved heterogeneity on regional level. Therefore, we have reverted to recent panel models as the nested error component model (Baltagi et al. 2001) to capture state and municipality heterogeneity and secondly different stochastic frontier models to figure out efficiency differentials, including the consideration of latent heterogeneity as with Greene's true random effects model (Greene 2005) respectively by including observable variables for the infrastructure environment (Battese and Coelli 1995).

Our findings provide new and unique insights for Mexican manufacturing on a very detailed regional base. Special emphasis has been given to obtain estimates for regional effects and efficiency scores for all municipalities and to provide relative regional rankings according to them. Remarkably, nested panel and stochastic frontier models lead to similar results and conclusions in this regard. Our results indicate that the underlying technology in the manufacturing sector is characterized by increasing returns to scale on municipality level. Predictions of regional-specific intercepts from the nested error component model show sustained differences between the states, primarily along the north-south divide. The respective signs of the predicted municipality- and state-effects typically move in the same direction, but the state-effects are clearly higher indicating a prominent role for factors at state-level to explain lagging regions in this model.

The different stochastic frontier model specifications reflect the same trend: the northern states operate more efficiently in manufacturing compared to the south of the country. There are still sustained differences in the economic structure, and southern municipalities appear to suffer from a lack of technical efficiency in comparison to the north. This phenomenon can be related to the geographical proximity to the U.S., such that the northern regions benefit from the connectivity to trans-border markets in the U.S. in terms of superior intermediate inputs and capital, spillovers such as knowledge- or technology transfer and competitive pressures fostering efficiency (learning by exporting effects). The traditional manufacturing belt with its less up-to-date technology and domestic market orientation is clearly lagging behind. The south is further marginalized; its economic structure is dominated by micro firms unable to exploit scale economies and low-skilled workforce. It is crucial to implement various types of skill upgrading and technology adoption programs in order to enhance productivity, as the lagging southern region may impede the development potentials of the still economically fragile country as a whole. A further explanation of lower productivity is related to the insufficient infrastructure - especially with regard to water - in the southern states in opposition to the northern regions. This implies the necessity of inter and intra regional infrastructure investments (such as in ports along the gulf to strengthen export opportunities to the U.S.) to improve the density and quality of the network to gain productivity.

Last but not least, both nested panel and stochastic frontier results show marked differences in the efficiency scores for municipalities both within the states and between the states. This implies that single ‘islands of excellence’ exist, i.e. municipalities ranking among the most efficient ones nationwide - but being located in one of the otherwise worst performing states of Mexico. This phenomenon illustrates that windows of opportunities for municipalities in the south exist and indicates perspectives for well-managed policies on the municipality-level.

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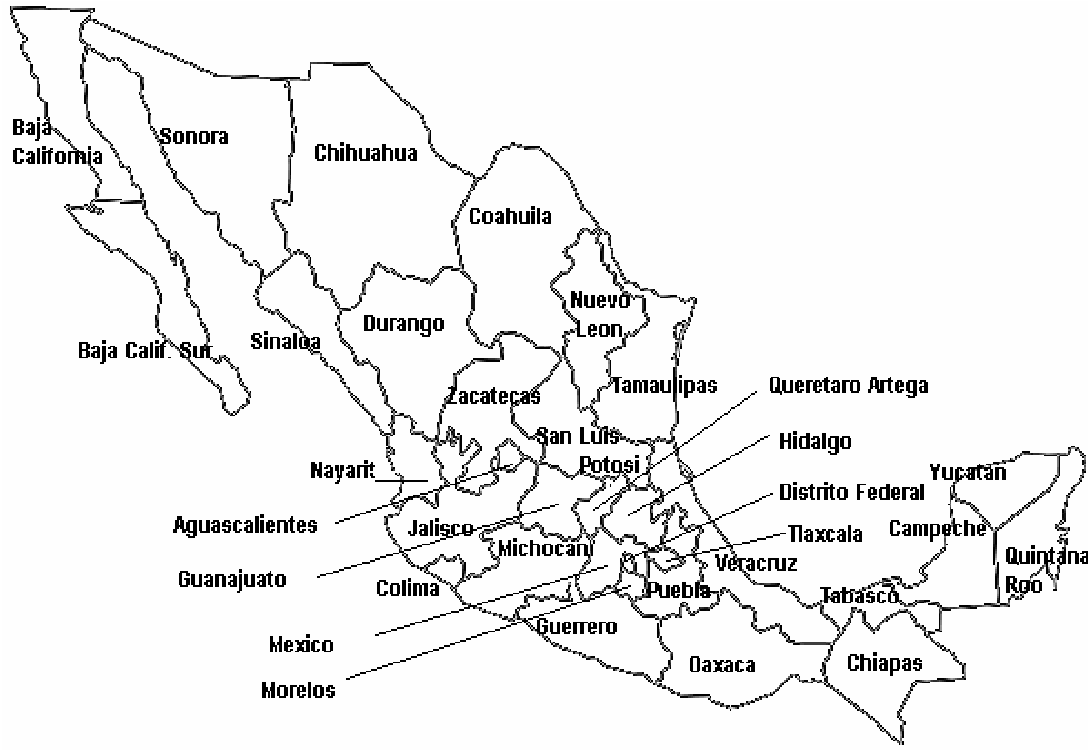
A) Figures

FIGURE 1 Map United Mexican States



B) Tables

TABLE 2 Regional Structure of Panel for 2004

State	Municipalities in respective state	Municipalities included in panel	Value added per employed person	Regional employment share
01 AG	11	9	89.954	0.015
02 BC	5	4	89.940	0.060
03 BCS	9	4	57.232	0.002
04 CAMP	11	9	27.976	0.003
05 COAH	38	32	91.231	0.052
06 COL	10	10	84.822	0.003
07 CHIS	119	98	27.244	0.008
08 CHIH	67	52	49.436	0.085
09 DF	16	15	109.729	0.097
10 DGO	39	35	32.272	0.018
11 GTO	46	46	79.739	0.054
12 GRO	79	70	20.22	0.010
13 HGO	84	77	59.123	0.017
14 JAL	124	122	57.952	0.079
15 MÉX	125	119	71.201	0.110
16 MICH	113	112	32.502	0.020
17 MOR	33	33	53.906	0.011
18 NAY	20	18	37.804	0.003
19 NL	51	47	20,307	0.079
20 OAX	570	346	65.559	0.011
21 PUE	217	203	79.954	0.052
22 QRO	18	17	35.864	0.023
23 QR	8	7	56.028	0.002
24 SLP	58	53	42.052	0.024
25 SIN	18	17	42.052	0.009
26 SON	72	46	64.322	0.031
27 TAB	17	17	118.860	0.005
28 TAMPS	43	40	48.960	0.052
29 TLAX	60	43	69.580	0.011
30 VER	212	183	50.327	0.028
31 YUC	106	103	19.030	0.020
32 ZAC	57	51	39.263	0.006
Total	2452	2038	-	-

Note: Column 2 presents the number of municipalities in the respective state for 2004; column 3 is valid for all periods, as the panel is balanced. Column 4 displays the average value added in Pesos per employed person.
Source: INEGI; own calculations

TABLE 3 Variable Means and Standard Deviations

Variable	Year	Mean	Standard deviation
Real value added	1989	217 964.30	1 378 776
	1999	348 798	1 804 466
	2004	448 916.90	2 226 472
Private Capital Stock	1989	522 740.60	3 362 531
	1999	509 510.20	2 476 162
	2004	555 059.90	2 849 740
Number of employed persons	1989	1 261.03	6 784
	1999	2 132.96	10 544
	2004	2 014.40	9 508
Proportion of HHs with Electricity Access	1989	0.78	0.20
	1999	0.89	0.11
	2004	0.93	0.08
Proportion of HHs with Water Access	1989	0.29	0.22
	1999	0.34	0.25
	2004	0.41	0.29

Note: Real series refer to the base period December 2003.
Source: INEGI, own calculations

TABLE 4 Estimates and Test Results from LS and Nested Error Components Models

	Translog Function		**Cobb-Douglas Function**	
	LS	Nested ECM	LS	Nested ECM
Capital fa	**.525**	**.503**	**.572**	**.528**
	.014 ***	.015 ***	.009 ***	.009 ***
Labor l	**.613**	**.637**	**.589**	**.615**
	.018 ***	.020 ***	.011 ***	.012 ***
Capital squared fa^2	**-.004**	**.006**	-	-
	.007	.007		
Labor squared l^2	**.04**	**.046**	-	
	.015 **	.015 **		-
FaL	**-.016**	**-.021**	-	-
	.010 *	.010 ***		
Constant	**-.281**	**-.331**	**-.241**	**-.298**
	.019 ***	.036***	.018 ***	.035 ***
σ_u	-	**.152**	-	**.155**
		.023 **		.023 **
σ_ε	-	**.648**	-	**.649**
		.007 **		.007 **
σ_μ	-	**.264**	-	**.26**
		.015 **		.014 **
R squared	.947	-	.718	-
Test: CRTS	F(3,6108): **426.33** ***	chi2(3): **779.28** ***	F(1,6111): **1240.96** ***	chi2(1): **786.45** ***
Test: Joint significance	F(5,6108) **21796.53** ***	Wald chi2(5) **70143.08** ***	F(2,6111) **54196.71** ***	Wald chi2(2) **70293.31** ***
Test: Cobb-Douglas vs. Translog ◆	F(3,6108): **47.92** ***	LR chi2(3): **64.5** ***		
Observations	6114	6114	6114	6114

Note: Variables have been rescaled to have unit means and have been transformed with natural logarithm. Coefficients can be interpreted as elasticities with respect to value added.

◆ The fixed effects part (i.e. the coefficient sets) of the NECM is differently specified in the Cobb-Douglas than in the Translog case which REML thus estimates as separate models. LR-tests for comparing models with different parameterizations of the FE-part are not possible then. Alternatively, models have been re-estimated with ML.

Standard errors are given in parentheses. * denotes significant at 10%-level; ** significant at 5%-level; *** significant at 1%-level.

TABLE 5 Ranking of Mexican Regions according to NECM

State	State Effect	State	Mean Municipality Effect
08 CHIH	0.2756	03 BCS	0.0209
26 SON	0.2709	26 SON	0.0177
05 COAH	0.1875	05 COAH	0.0176
19 NL	0.1707	08 CHIH	0.0160
15 MÉX	0.1390	22 QRO	0.0156
28 TAMPS	0.1218	01 AG	0.0115
22 QRO	0.0883	19 NL	0.01
24 SLP	0.0467	28 TAMPS	0.0092
14 JAL	0.0417	04 CAMP	0.0065
01 AG	0.0345	15 MÉX	0.0035
03 BCS	0.0278	24 SLP	0.0027
04 CAMP	0.0194	09 DF	0.0021
09 DF	0.0106	27 TAB	0.0012
27 TAB	0.0068	14 JAL	0.0010
17 MOR	0.0011	17 MOR	0.0001
06 COL	-0.0054	29 TLAX	-0.0005
29 TLAX	-0.0075	13 HGO	-0.0006
02 BC	-0.0129	16 MICH	-0.0011
13 HGO	-0.0149	30 VER	-0.0012
23 QR	-0.0185	07 CHIS	-0.0015
10 DGO	-0.0302	06 COL	-0.0016
25 SIN	-0.0309	21 PUE	-0.0026
18 NAY	-0.0391	10 DGO	-0.0026
16 MICH	-0.0406	20 OAX	-0.0030
07 CHIS	-0.0484	11 GTO	-0.0040
11 GTO	-0.0612	32 ZAC	-0.0052
30 VER	-0.0745	25 SIN	-0.0055
32 ZAC	-0.0881	18 NAY	-0.0065
21 PUE	-0.1739	31 YUC	-0.0067
12 GRO	-0.2269	23 QR	-0.0080
31 YUC	-0.2284	02 BC	-0.0097
20 OAX	-0.3412	12 GRO	-0.0098

Note: Calculations are based on BLUPs obtained from the Translog NECM.
Rankings follow a decreasing order.
The municipality effects represent the average of the respective municipality effects over all municipalities in the respective state.

TABLE 6 Best and Worst Ranking Municipalities from NECM

Municipality	State	Regional Effect NECM
	Best Performing Municipalities	
26027 Fronteras	26 SON	0.704
26067 Villa Hidalgo	26 SON	0.676
8053 Praxedis G. Guerrero	08 CHIH	0.655
5014 Jiménez	05 COAH	0.623
8065 Urique	08 CHIH	0.617
26039 Naco	26 SON	0.604
26014 Baviácora	26 SON	0.588
32025 Luis Moya	32 ZAC	0.587
21040 Cuautinchán	21 PUE	0.585
26016 Benjamín Hill	26 SON	0.585
	Worst Performing Municipalities	
20487 Santiago Tenango	20 OAX	-0.727
20564 Yutanduchi de Guerrero	20 OAX	-0.739
31074 Tahmek	31 YUC	-0.748
20511 Santo Domingo Nuxaá	20 OAX	-0.872
20126 San Cristóbal Amatlán	20 OAX	-0.865
20270 San Miguel Huautla	20 OAX	-0.924
20054 Magdalena Zahuatlán	20 OAX	-0.981
20201 San Juan Juquila Vijanos	20 OAX	-0.996
20230 San Lorenzo Victoria	20 OAX	-1.022

Note: Aggregated regional effects represent the combined state- and municipality-level effect according to BLUPs from the NECM. Shown here are the municipalities with the ten highest and ten lowest figures.

TABLE 7 Results from Stochastic Frontier Model I and II

	Model II	Model I
Capital fa	**.521**	**.519**
	.010***	.009 ***
Labor L l	**.622**	**.629**
	.014***	.013 ***
Capital squared fa^2	**.016**	**.007**
	.003***	.003 **
Labor squared l^2	**.065**	**.0565**
	.006***	.006 ***
FaL	**-.035**	**-.030**
	.004***	.003 ***
Constant	**-.006**	
	.021	
Mean random parameter α_i		**.108**
		.023 ***
Electricity elhh	.**506**	**-**
	.438 ***	
Water whh	**-.474**	**-**
	.043	
Variance parameter λ	**.693**	**.784**
	.028 ***	.008 ***
Variance parameter σ_u	**.453**	**.933**
	.020 ***	.0463 ***
Standard deviation random parameters		**.285**
		.007 ***

TABLE 8 Average State Efficiency from Model I and II

State	Average State Efficiency Model I	Average State Efficiency Model II
26 SON	0.70	0.71
08 CHIH	0.69	0.71
19 NL	0.69	0.69
05 COAH	0.69	0.68
15 MÉX	0.68	0.67
22 QRO	0.68	0.67
28 TAMPS	0.68	0.68
03 BCS	0.68	0.66
01 AG	0.68	0.65
04 CAMP	0.68	0.65
24 SLP	0.67	0.65
14 JAL	0.67	0.65
17 MOR	0.67	0.64
13 HGO	0.67	0.63
27 TAB	0.67	0.63
07 CHIS	0.67	0.63
16 MICH	0.67	0.63
25 SIN	0.67	0.63
06 COL	0.67	0.63
23 QR	0.67	0.63
10 DGO	0.67	0.63
09 DF	0.67	0.63
29 TLAX	0.66	0.63
30 VER	0.66	0.62
02 BC	0.66	0.62
11 GTO	0.66	0.62
32 ZAC	0.66	0.61
18 NAY	0.66	0.62
21 PUE	0.65	0.59
31 YUC	0.65	0.58
12 GRO	0.65	0.57
20 OAX	0.64	0.55

TABLE 9 Best and Worst Performing Municipalities from Model I and II

Municipality	State	Year	Efficiency score model I	Efficiency score model II
		Best Performing Municipalities		
8065 Urique	08 CHIH	2004	0.906	0.874
10010 Hidalgo	10 DGO	1999	0.901	0.879
21040 Cuautinchán	21 PUE	1999	0.886	0.918
12041 Malinaltepec	12 GRO	1989	0.883	0.839
26067 Villa Hidalgo	26 SON	1989	0.879	0.889
32025 Luis Moya	32 ZAC	1989	0.873	0.914
30152 Tampico Alto	30 VER	2004	0.888	0.851
21145 S. Seb Tlacotepec	21 PUE	1999	0.886	0.844
21089 Jopala	21 PUE	1989	0.885	0.813
21032 Cohetzala	21 PUE	1989	0.888	0.808
		Worst Performing Municipalities		
11006 Atarjea	11 GTO	1999	0.233	0.267
24047 Villa de Guadalupe	24 SLP	2004	0.213	0.363
19047 Hidalgo	19 NL	2004	0.222	0.412
20126 S. Crist. Amatlán	20 OAX	1999	0.236	0.213
20201 S. J. Juq. Vijanos	20 OAX	1999	0.212	0.174
31026 Dzemul	31 YUC	1989	0.193	0.381
31086 Tepakán	31 YUC	1989	0.176	0.322
26049 Quiriego	26 SON	1989	0.110	0.317
31074 Tahmek	31 YUC	1989	0.084	0.236
31105 Yaxkukul	31 YUC	1989	0.038	0.273

Note: Ranking follows the scores from Model I in a decreasing order. The respective scores from Model II for the respective municipalities are provided by the last column.